UNIVERSITY OF OKLAHOMA

GRADUATE COLLEGE

OVERALL AND GENDERED EFFECTS OF POST-RELEASE SUPERVISION: A PROPENSITY SCORE ANALYSIS

A THESIS

SUBMITTED TO THE GRADUATE FACULTY

in partial fulfillment of the requirement for the

Degree of

MASTER OF ARTS

By

AMY DIANN MILLER
Norman, Oklahoma
2017

OVERALL AND GENDERED EFFECTS OF POST-RELEASE SUPERVISION: A PROPENSITY SCORE ANALYSIS

A THESIS APPROVED FOR THE DEPARTMENT OF SOCIOLOGY

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Dedication

I dedicate this thesis to my mother, DiAnna Miller, for her love and support throughout my education and my life.

Acknowledgements

Firstly, I would like to express my sincere gratitude to my advisor Dr. Trina Hope for the continuous support of my M.A. study and for her patience, motivation, and immense knowledge. Her guidance helped me throughout the research and writing of this thesis in addition to the many questions I had during my entire time in the graduate program.

Besides my advisor, I would like to thank my committee member Dr. Cyrus Schleifer for his insightful comments and helpful advice not only on this thesis but while working together on a paper publication, my summer fellowship, and as his teaching assistant.

I would also like to thank my committee member, mentor, and friend Dr. Susan Sharp. Throughout my entire academic career, Dr. Sharp has been invested and dedicated to helping me become a better student, researcher, and person. Her recommendation to attend graduate school and pursue my master's degree, changed the trajectory of my life. For her support, mentorship, and friendship, I am forever grateful.

Finally, I would like to thank my cohort, Kara Snawder and Chelsea Elam as well as Melissa Jones, Taylor Thompson, and many, many other graduate students for their support and helpfulness throughout my time at OU.

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Abstract

The number of people in the correctional population has skyrocketed in recent decades, with the majority being supervised within the community after release. The female correctional population, which has historically been small, has also increased in number. The purpose of this paper is to investigate the overall and gendered effects of post-release supervision. Using propensity score matching, I discover that post-release supervision is associated with a 4% to 4.5% reduction in recidivism, measured by both rearrest and reconviction. Men echo the overall trend while the numbers for women are much smaller and nonsignificant. Indeed, among supervised females we anticipate no significant reduction in recidivism measured by rearrest. With the amount of time, energy, and money spent on supervising offenders after release, future studies should further this research by conducting a cost benefit analysis and investigating the most effective types of supervision in reducing recidivism.

Chapter 1: Introduction

The number of people under correctional authority within the United States has sky rocketed in recent years, reaching over 6.8 million at the end of 2014. Put another way, about 1 in 36 adults are in the criminal justice correctional population (Kaeble et al. 2016). Over the past four decades, the US has begun a method of gross incapacitation, the strategy of imprisoning offenders in large numbers, sometimes with little regard for factors such as criminal histories (Walker 2011). This strategy has led to an explosion within the criminal justice system and the correctional population, affecting both male and female populations. The number of male and females admitted to prisons has grown substantially in recent decades (Carson 2014; Carson and Golinelli 2013; Hester 1987) as has those under correctional authority and supervision. In 2014, over 60% of those under correctional authority were under community supervision, meaning they were not physically confined but rather supervised and monitored by the criminal justice system (Kaeble et al. 2016). The purpose of this paper is to examine the relationship between post-release supervision and recidivism, and to investigate any gendered differences.

In the past, females have comprised a small percentage of the criminal justice population, but their numbers are growing. Between 1991 and 2011, females admitted into state prisons for violent offenses increased 83% and the number of females entering prisons for property crimes grew from 10,300 in 1991 to 26,000 in 2013 (Carson 2014; Carson and Golinelli 2013). Of those on probation during 2014, almost a quarter were female and, of those on parole, 1 in 8 were women (Kaeble, Maruschak and Bonczar 2015), making women in the criminal justice system an important, but understudied, topic (as noted by MacKenzie 2006 and Wattanaporn and Holtfreter 2014).

While female incarceration has increased at the national level, some states are incarcerating at higher rates than others. Indeed, Oklahoma has the highest female incarceration rate at 151 per 100,000 (Carson 2016). In contrast, Florida is more comparable with the national average of 64 per 100,000 with 71. Furthermore, Florida's male incarceration rate is also very similar to the nation's average, 946 compared to 863 per 100,000 (Carson 2016). Because its overall criminal characteristics are similar to those at the national level, Florida is a fitting site to study the relationship between post-release supervision and recidivism for both men and women.

Defining Supervision and Recidivism

In Florida, post-release supervision includes supervision such as parole, conditional release, conditional medical release, control release, and addiction recovery supervision (Florida Commission on Offender Review (FCOR) 2014). Perhaps the most known form of supervision is parole. This is when an offender is released before their court-imposed sentence expires, with specific conditions regarding how they will be supervised by the Florida Department of Corrections (FDOC). For inmates with sentences for specific crimes such as violent or sexual crimes, conditional release is a type of mandatory post-prison supervision. Inmates who are terminally ill or permanently incapacitated, may be released on conditional medical release if they do not represent a danger to others. Other times, offenders may be released with supervision in order to maintain a prison population between 99 and 100 percent capacity. Lastly, addiction recovery supervision is a mandatory post-prison supervision for inmates with substance abuse histories or addiction, given they have not been convicted of certain crimes such as violent offenses or drug trafficking (FCOR 2014). This study offers a broad view of the relationship between supervision and recidivism by including all supervision types into one category of post-release supervision[1]

Recidivism or reoffending is “the act of reengaging in criminal offending despite having been punished” (Pew Center 2011:7). In practice, researchers may define recidivism in a variety of ways. Recidivism can be defined as whether an offender is rearrested (Andersen and Wildeman 2015), reconvicted (Mears, Cochran and Bales 2012), or re-incarcerated (Barrick, Lattimore and Visher 2014; Staton-Tindal et al. 2011) and can include new crimes and/or technical violations to the terms of their parole. Compared to rearrest, reconviction is a more conservative measurement of recidivism, as not all who are rearrested will actually be reconvicted. In the present study, I use two binary variables to capture recidivism, rearrest and reconviction.

[1] Due to data limitations, I am unable to examine the supervision types individually.

In addition to the definition of recidivism, a follow-up period must be determined. Some studies use a one or two year follow-up period (Hedderman and Jolliffe 2015; Kennealy et al. 2012; Matheson, Doherty and Grant 2011). However, if too short of a period is chosen, researchers run the risk of having too few offenders who recidivate or failing to capture a large portion of offenders who do reoffend. Indeed, over 20% of released offenders who are not rearrested within a two year time frame are rearrested during the third year (Durose, Cooper and Snyder 2014). Furthermore, 67.8% of prisoners are rearrested within three years of release, compared to 76.6% within a five-year period (Durose, Cooper and Snyder 2014). Following the standard set by past research (Bales and Piquero 2012; Mears, Cochran and Bales 2012; Pelissier et al. 2003; Scott et al. 2016), I employ a follow-up period of three years.

Chapter 2: Past Literature

Supervision and Recidivism

Many studies have been conducted on the effects of imprisonment on recidivism, often in contrast to community sentences (Bales and Piquero 2012; Cullen, Jonson and Nagin 2011; Gaes, Bales and Scaggs 2016; Hedderman and Jolliffe 2015; Jolliffe and Hedderman 2015). For example, prison has been found to have a criminogenic effect, especially for property and drug offenders, when compared to intensive probation (Mears, Cochran and Bales 2012). However, less has been done on post-release supervision.

Research that has examined the types of supervision after release often focus on specific types of supervision programs (Wikoff, Linhorst and Morani 2012). Drug treatment courts in North Carolina have been found to reduce rearrest rates for offenders (Gifford et al. 2014) and completion of treatment regimens, which are a series of programs or interventions that take place while the offender is incarcerated and on parole, were found to decrease rearrests in Iowa (Peters et al. 2015). In contrast, a 90-day post-release service program in New York City found no differences in recidivism between participants and nonparticipants (White et al. 2012). These studies, while helpful in understanding the utility of specific programs, are limited in the extent they can shed light on the effects of post-release supervision more broadly.

Research investigating gendered differences in the relationship between supervision and recidivism is even more limited. Once again, past studies have examined the gendered effects of incarceration (Mears, Cochran and Bales 2012; Staton-Tindal et al. 2011; Alemango 2001) or gender specific treatment programs which take place while the women are confined in prison (Pelissier et al. 2003) or after release (Evan et al. 2013). Women-only programs seem to have positive, short term outcomes such as lower rearrest rates during first year after treatment, but long term outcomes, such as incarceration after third year of treatment, show no advantages (Hser et al. 2011). These findings are mixed and incomplete and more needs to be done regarding the broad category of post-release supervision, rather than specific programs.

The findings from these different supervision programs are not only mixed and limited, leading to an ambiguous and incomplete assessment of post-release supervision, but the majority of these studies fail to offer a broad, encompassing look at the effectiveness of post-release supervision as a whole. Furthermore, focusing on specific programs has limited the sample size of past studies as well as the ability to generalize outside of unique situations. This paper aims to fill this gap by examining the effects of post-release supervision, defined to include a variety of types of supervision within the entire state of Florida, which allows my analytic sample size to be quite large with 141,338 offenders.

Gendered Pathways

Because women commit such a small percentage of crime compared to men, historically most criminology theories and research were based on males and paid little to no attention to females (Chesney-Lind 1997; MacKenzie 2006). Beginning in the 1970s with the women's movement, female offenders began to receive more attention and during the 1980s and 1990s distinctions between men and women offenders began to be investigated (Britton 2000). Studying gendered differences in the life experiences and circumstances for "gendered differences in type, frequency, and context of criminal behavior" can shed light on the different pathways into crime (Steffensmeier and Allan 1996:473). Many researchers, especially feminist scholars, have made great strides in this area, by investigating common themes present in the lives of girls and women and how those characteristics interact with the criminal justice system. Although much more research is needed to address critical questions about women offenders (Sharp and Hefley 2007), great strides have been made and many gendered pathways into crime have been found.

In her research using case biographies, Daly (1992; 1994) found five pathways for women into felony court. First, the street women are characterized by abusive home lives, poverty, drugs, and well-developed criminal records. In contrast, harmed and harming women are often abused as children and may have psychological problems which contribute to their inability to cope with their current situation and their use of drugs or alcohol. In the third pathway, battered women are often in a violent relationship with a man or may have recently ended such a relationship. Drug-connected women use or sell drugs, often with family members or boyfriends, which leads them to felony court.

“Other” women, who do not fit into the previous categories, seem to find themselves in felony court due to a need or desire for money (Daly 1994; 1992).

While these pathways define women’s entry into court, they do not completely characterize the experience for men. Some overlap, such as drug connections do exist between women’s and men’s pathways, but important distinctions remain (Daly 1994). For example, the drug-connected women recently began using or selling drugs while in relationships with boyfriends, and have no or minimal prior criminal history. In contrast, the drug-connected men’s drug use or sales are not linked to their relationships with their girlfriends (Daly 1994). This shows one of the many distinctions between the criminal pathways for men and women.

Other research has also found a connection between women’s pathways into crime and their relationships with male partners (Hser, Anglin and McGlothlin 1987; Jenkot 2016; Sharp 2014). In Sharp’s (2014) study of female offenders from Oklahoma, she found that being in relationships with criminal men is one common pathway into crime for women. These relationships not only introduced or encouraged the women to participate in illegal activities such as using, selling, or manufacturing drugs, but also led to the incarceration of some women if they felt obligated to falsely admit to or overstate their part in a crime in order to keep their boyfriends out of prison (Sharp 2014). Other pathways include poor, marginalized women from families with multigenerational incarceration and women with extensive histories of childhood and adulthood abuse (Sharp 2014). These pathways, as will be discussed below, are not discrete.

Many researchers, including feminist scholars and criminologists, have found several different categorization systems and schemes for the unique experiences of women entering into crime (Brennan et al. 2012; Chesney-Lind 1997; Chesney-Lind and Shelden 1998; Richie 1996; Rosenbaum 1979; Wattanaporn and Holtfreter 2014). Some pathways have focused not only on gender differences in pathways to crime, but also racial differences (Richie 1996), the type of crime committed (Brennan et al. 2012), and the role of mental disorders (Robbins, Monahan and Silver 2003). Indeed, researchers have called for increased attention not only to gender, but also to other intersecting inequalities which uniquely affect the experiences of women and girls (Burgess-Proctor 2006; Durfee 2016).

From these pathways, common themes emerge such as the role of abuse, drugs, and relationships. Both childhood and adulthood physical, sexual, and emotional abused are prevalent among women and girl offenders and play a role in their offending (Belknap and Holsinger 2006; Elliot et al. 2010; Fuentes 2014). The trauma from abuse, coupled with the lack of resources available inside and outside of prison, increases recidivism among females (Fuentes 2014). Drugs often interact with the unresolved trauma for female offenders. To be sure, 78% of injecting drug use among female offenders has been linked to childhood adverse experiences such as psychological, physical, and sexual abuse and household dysfunction like substance abuse, mental illness, and criminal behavior (Felitti 2003; Felitti 1998). Upon release, studies show that drug-abusing women are more likely to report needing housing, counseling, support, and assistance (Alemagna 2001).

Because of this overlap and sometimes succession of events, the gendered pathways into crime are not mutually exclusive, and women may fall into any combination of pathways (Sharp 2014). A woman may come from a poverty stricken family which is characterized by multi-generational incarceration, gets introduced to drugs by a boyfriend, and later abuses drugs as a way to cope with a history of unresolved trauma. This not-so-uncommon illustration shows multiple pathways into crime for a single woman, emphasizing that the pathways described above connect and intersect for some offenders. Although the crime on the record may be the same for men and women, the reasons for committing the crime differ and the paths into offending diverge.

Women's Reoffending

Past research has illuminated the gendered difference of pathways into crime, but fewer studies have focused on differences in reoffending. In addition to the traditional constraints offenders face when attempting to reintegrate into society, women's barriers are exacerbated by gendered constraints as well. Constraints such as lack of social and human capital uniquely characterize the pathways for women’s reoffending (Salisbury and Van Voorhis 2009). Furthermore, characteristics that place offenders at a severe disadvantage in the reentry process, such as being of color, having drug-related offenses, having family members involved in the criminal justice system, being survivors of physical and/or sexual abuse, and having mental health problems are very prevalent among female prisoners (Cloyes et at. 2010; Greene and Pranis 2012). Therefore, not only do women face unique pathways into prison, but they encounter distinctive challenges after release.

Employment, housing, transportation, economic problems, and family issues affect both male and female offenders (Makarios, Steiner and Travis 2010), but may be especially difficult for women reentering society (Ortiz 2014; Garcia 2016; Matheson, Doherty and Grant 2011). Low skill, physically demanding jobs such as construction and maintenance are often options for men, but not women, leading women to work low-skill, secondary labor market jobs (Sharp and Ortiz 2016; Visher, Debus, and Yahner 2008). Having a conviction makes finding suitable housing a challenge because many landlords and apartment companies refuse to rent to a former felon. This is made especially difficult for female offenders who are mothers.

Nationally, about two-thirds of female prisoners are mothers, and 4 in 10 mothers were living in single-parent household one month prior to arrest (Glaze and Maruschak 2008). Many are reunited with their children upon release even though “getting full responsibility too soon could sabotage the chance of successful reintegration” (Sharp 2014:116). Therefore, finding safe and suitable housing is not only important for their well-being, but for their children as well. Similarly, while transportation is often difficult for many recently released offenders due to their lack of financial resources and the absence of public transportation in many cities, women offenders who are mothers require reliable transportation not only for themselves but also for their children. While some of these factors overlap with men, many are unique challenges mothers are presented with upon release and struggle to overcome.

Some studies have focused on specific aspects that reduce the risk of recidivism for women. Getting custody of children, engaging in a self-help activity, and environmental support all significantly decrease the risk of recidivism for women leaving jail (Scott et al. 2016). Furthermore, maintaining contact with family while in prison is associated with higher levels of support after release and lower likelihood of recidivism (Barrick, Lattimore and Visher 2014). Serious mental illness (Cloyes et al. 2010), good-quality relationships (Cobbina, Huebner and Berg 2012; Greiner, Law and Brown 2015), and services such as childcare, transportation, and housing (Peugh and Belenko 1999) more strongly impact women’s reoffending compared to men’s, showing that women’s recidivism factors diverge from those affecting men and echo their gendered pathways into crime.

Others have examined the effectiveness of specific programs developed especially for women and found that they were effective in reducing returns to prison (Gehring, Van Voorhis and Bell 2010; Matheson, Doherty and Grant 2011; Stanley et al. 2015). However, these programs are rare and, due to size and financial constraints, can only include a small number of women offenders. Therefore, most women are not supervised through gender-specific programs. Rather, they are supervised through a state or federal department of corrections, often with little emphasis on gendered differences. Even tools used to gauge offenders' risks and needs for successful reentry, such as the Level of Supervision Inventory-Revised, fail to consider the specific challenges women face, and therefore have only partial success (Bonta, Pang and Wallance-Capretta 1995; Holtfreter and Morash 2003; Reisig, Holtfretter and Morash 2006). These studies are helpful in showing that gender-specific reentry and supervision efforts can effectively reduce recidivism among women.

Even so, they are limited to the analysis of specific programs and offer only a small snapshot of the effects of post-release supervision, failing to speak to its effectiveness more broadly. This paper, using data from the entire state of Florida, is able to investigate the relationship between supervision and reoffending outside of a specific program and offer a more encompassing picture of the process overall. Therefore, I aim to answer two research questions.

1) What is the relationship between post-release supervision and recidivism?

2) Is this relationship stronger or weaker for female offenders?

I expect that post-release supervision will have a negative relationship with recidivism. Put another way, I expect offenders who are supervised after release to have lower rates for both rearrest and reconviction. Furthermore, I expect to find gendered differences. Since few gender-specific programs exist, especially within state level criminal justice systems, that address the unique challenges faced by women after release (Bloom et al. 2002; Bloom and Covington 1998; Schram et al. 2006), I expect the relationship between post-release supervision and recidivism to be especially weak for females when compared to males.

Chapter 3: Data and Methods

The data for this study come from the *Criminal Recidivism in a Large Cohort of Offenders Released from Prison in Florida, 2004-2008.* These data, collected by the Urban Institute, were gathered from two sources. First, criminal history records from Florida's DNA database, which is managed by the Florida Department of Law Enforcement were used and then docket information accessed through the FDOC was gathered. Merging the information from these two sources created a dataset, which after adjusting for missing cases[2] is narrowed slightly to 141,338. These cases involve FDOC offenders released between January 1996 and December 2004. The study allows for a three-year follow-up period and captures two measures of recidivism: rearrest and reconviction. The universe for this study is all offenders released between January 1996 and December 2004 from the Florida Department of Corrections.

Outcome and Predictor Variables

My outcome of interest is recidivism following a three-year follow-up period and is measured by two variables. Two dichotomous outcome variables *rearrest* or *reconviction*, are coded as 1 if the offender was rearrested or reconvicted and 0 otherwise. The predictor or treatment variable is *post-release supervision.* This binary indicator will be the treatment variable in my

[2] For this analysis, I utilize list-wise deletion on the control variables which reduces my sample by 15,364 cases (9.8%).

propensity score matching analysis. This means it is the outcome of my matching, logit model and the key predictor of my matched sample, described below.

Control Variables in the Logit Model

I include a number of demographic and crime-related variables. To account for gendered differences, I incorporate a binary *female* variable and to capture racial variation among the offenders, I include *White* where 1 indicates white and 0 indicates otherwise[3]. Additionally, a binary ethnic variable *Hispanic* is used and I control for *high school* education by having a binary indicator for individuals who completed twelve or more years of schooling (coded 1) compared to individuals who have not (coded 0). *Employment status* is a categorical variable capturing unemployed, full-time employment, part-time employment, and other[4]. For analysis, this variable is treated as a series of dummy variables with full-time employment as the reference category.

For crime variables, the dataset includes information on the type of crimes for which respondents were imprisoned. The *offense category* variable captures whether the offender's most serious offense was a violent, property, drug, or other crime. With this information I created a series of binary variables with violent crime as the reference category. Since past research shows that the presence of DNA in the law enforcement computer system affects recidivism

[3] Other than "white" and "black" no other racial group makes up more than 2% of the sample. Therefore, I dichotomize this variable.
[4] The "other" category includes statuses such as student, incarcerated, unemployable, and temporarily not working.

(Bhati 2010b), I control for this possibility by including a binary variable for whether or not the respondent is in the *DNA bank*. I also include *age at release* and *year of release* as these may affect the likelihood of being supervised (Bonham, Janeksela and Bardo 1986). *Year of release* is the calendar year the offender was released ranging from 1996 to 2004. This variable is minimum subtracted so that 0 means the offender was released during 1996 and 8 means the offender was released during 2004.

The dataset also contains a count measure of the number of years or *time served*. Since this is a core variable of interest, I transform this measure into four indicators: less than 1 year, at least 1 but less than 2 years, at least 2 but less than 5 years, and 5 or more years. I treat this as a series of dummy variables in the analysis with less than 1 year as the comparison category[5]. Lastly, to account for criminal history, *prior arrests* ranges from 0 to 13 or more arrests and is treated as a continuous variable.

Interactions in the Logit Model

Six interactions are included within the propensity score matching model. Past research has consistently shown that women not only commit less crime than men overall, but also that gendered differences exist in the types of crimes committed (Steffensmeier and Allan 1996). Therefore, I interact the *female* indicator with each of the *offense category* dummy variables.

[5] Models are robust to treating this variable as continuous with no significant differences in the results.

Furthermore, past research shows there are often educational differences between men and women offenders (Harlow 2003), and therefore I interact *female* with *high school.* Thirdly, the type of crime committed affects the likelihood of having DNA in the law enforcement system (Biancamano 2009). To account for this, I interact *offense category* with *DNA bank.*

When examining the likelihood of supervision, the number of prior arrests, along with the type of crime may lead to differential chances of being supervised. For example, an offender with 13+ prior arrests who committed a violent crime may be more likely to be supervised than an offender with 0 prior arrests who committed a property crime. Therefore, I interact *prior arrests* with *offense category*. Fifthly, since the amount of time served is often affected by the offense committed, I interact the *offense category* variables with *time served*. Lastly, the amount of *time served* in addition to an offender's *age at release* may affect supervision and I include this interaction as well.

Table 1 presents summary statistics for the variables in this analysis. I include the averages for the whole sample as well as gender specific subsamples. The significance tests represent a two sample *t*-test of the mean difference between men and women in the sample, as signified by a (+) in the last column. As expected, we see that females make up a small portion (9.3%) of the overall sample. The majority of the sample is non-white, with 45.4% being white. The most common offense committed is property crimes (32.6%), followed by violent crimes (30.5%), drug crimes (27.1%), and then other types of crimes (9.8%). The majority of the overall sample was full-time employed upon being incarcerated (54.5%) and the average number of prior arrests is 5.6. The sample is mostly undereducated, with just slightly more than one-fourth (28.3%) having a high school education or more. The average age at time of release is 33.5 years with 35.4% being supervised after release. Over half of the sample is rearrested within the three-year follow-up period (57.1%) while less than half are reconvicted (41.4%).

[Table 1 about here]

Table 1 also shows a number of significant gender differences. Significantly more females are white (46.9% versus 42.0%) while significantly more males are Hispanic (6.0% versus 2.7%). While violent is the most common crime type for men (31.3%), the most common crime committed by women is a drug crime (36.6%). Interestingly, more men report being full-time employed (57.2% versus 28.4%) while more women report being unemployed (59.7% versus 27.4%). Consistent with committing more violent crimes, a higher percentage of men spent 5 or more years incarcerated (13.8% versus 4.9%) while a higher percentage of women spent less than 1 year incarcerated (44.7% versus 29.9%). More men, compared to women, are supervised after release (36.4% versus 25.7%) as well as rearrested (58.2% versus 47.1%) and reconvicted (42.4% versus 31.7%). As expected, there are many gendered differences between the offenders. This suggests that there are gendered pathways into crime, which warrant a gendered examination of the effects of post-release supervision.

Statistical Approach

I use propensity score matching (PSM) to mimic randomized assignment by identifying “for each individual in a treatment condition, at least one other individual in a comparison condition that ‘looks like’ the treated individual on the basis of a vector of measured characteristics that may be relevant to the treatment and response in question” (Apel and Sweeten 2010:543). Observational data often lacks the characteristic of randomization, which ensures that the groups are balanced on unobservable differences, the standard for determining statistical causation. Due to practical or ethical reasons, randomization of treatment may be impossible for some research questions (Apel and Sweeden 2010). Therefore, propensity score matching helps to mimic experimental techniques by balancing observable characteristics between the control and treatment groups (Rosenbaum and Rubin 1983) allowing for statements that are closer to causality than other analytic techniques (Guo and Fraser 2015; Rosenbaum and Rubin 1983).

PSM has three steps. First, a logit model is estimated to generate the probability of each individual in the sample to be supervised. These probabilities are called the propensity scores. Secondly, supervised individuals are matched to individuals who have similar propensities to be supervised, but were not. These matched individuals create a matched sample that allows for formal comparisons between the groups, after an assessment of the covariate balance. Thirdly, the average treatment effect and the average treatment effect on the treated are computed and interpreted, which are explained below (Caliendo and Kopeinig 2008; Guo and Fraser 2010; Rosenbaum and Rubin 1983; Suh 2016).

Step 1: Logit Model

First, a logit model is estimated for the propensity to receive treatment based on an exhaustive list of relevant variables. That is, each individual in the sample receives a probability, ranging from 0 to 1, of their likelihood to be supervised after release according to a predictive regression model. A propensity score of 0 indicates that, based on relevant variables, the offender has a 0% predicted probability of being supervised after release. In contrast, a propensity score of 1 indicates the offender has a perfect, certain probability being supervised. In practice, propensity scores almost always fall between 0 and 1. In the present study, the following logistic regression is used to obtain the propensity scores which range from 0.08 to 0.91.

$$\ln\left(\frac{\Pr(Super = 1)}{1 - (\Pr(Super = 1))}\right) = \beta_0 + \beta_1(Female) + \beta_2(Controls) + \beta_3(Interactions)$$

In this logit model, the natural log of the odds of being supervised after release is the outcome variable. This number, ranging from 0 to 1 for each offender, is the propensity score. The model intercept is captured by the vector β_0 and the vector β_1 captures the coefficient for the effect of being female. The coefficients for the control variables are captured in β_2 while β_3 contains the effects of the interactions. The results for the logit model predicting the propensity scores are shown and described in Table 3 in Appendix D.

Step 2: Propensity Score Matching

After the propensity scores are generated by the logit regression, I match each supervised offender with one unsupervised offender who has the closest propensity score. That is, for each supervised offender, whichever unsupervised offender has the nearest propensity score will be its match. Nearest is defined as the smallest difference in absolute magnitude. This technique is called 1-to-1 nearest neighbor matching and can be done both with and without replacement (Caliendo and Kopeinig 2008). When completed without replacement, each supervised unit must be matched with a different unsupervised unit. Since each matched pairing must be unique, this ensures that the numbers of supervised and unsupervised units are equal. When completed with replacement, two supervised units may be matched with the same unsupervised unit, if that is the closest propensity score. This method allows for the subsample of matched supervised units to be larger than the subsample of matched unsupervised units. In this paper, I complete 1-to-1 nearest neighbor matching both with and without replacement.

Next, it is important to compare the covariates across the supervised and unsupervised groups both before and after the matching. Ideally, since the objective of PSM is to create groups that are similar in order to mimic randomization, after matching there should be little to no significant differences between the supervised and unsupervised groups across all the variables and interactions in the matching model. Table 2 shows the covariates as summary statistics before matching, after PSM without replacement, and after PSM with replacement. Each of the unsupervised columns is compared to the supervised column with a two-sample *t*-test used to signal any significant differences between the groups. Since my sample size is large, I choose to be conservative with my p-value and only report significant differences at the $p<0.001$ level.

First, I compare supervised offenders with unmatched, unsupervised offenders, highlighting significant differences between the groups before matching. Females comprise about 7%.of the 50,074 offenders who are supervised after release in contrast to 11% of the 91,259 unsupervised offenders. This is a statistically significant difference that contributes to the imbalance between the supervised and unsupervised groups. Indeed, there are 34 statistically significant differences between the supervised group and the unmatched, unsupervised group which demonstrates the need for matching.

The next column shows the covariates after matching without replacement. Here, every supervised offender is matched with exactly one unsupervised offender, without replacement. This makes each pairing unique and makes the subsample sizes the same at 50,074 offenders in each group. With this matching strategy, the balance between the groups improves but is still unequal. Of those who are supervised, about 7% are female. However, of those in the unsupervised, matched without replacement subsample, about 8% are female, a statistically significant difference. Indeed, even after this matching method 28 statistically significant differences remain. Additionally, the Rubin's B statistic, which should be under 30 to indicate a well-balanced group (Rosenbaum and Rubin 1983; Rubin 2001), is above that threshold at 44.3. Also, the Rubin's R statistic, which indicates a well-balanced group if the statistic is below 1.5 (Rosenbaum and Rubin 1983; Rubin 2001), is above the threshold at 1.58. This demonstrates the need for another matching method.

[Table 2 about here]

Finally, we examine the matched with replacement subsample. Here, each supervised offender is matched with an unsupervised offender. However, the pairings are not unique and an unsupervised offender may be matched with more than one supervised offender. This is showcased in the subsample sizes. There are fewer offenders in the unsupervised subsample because they may be matched more than once.

Now, we can see that balance across the groups is achieved. There are 7% females in both the supervised and the matched with replacement, unsupervised group. Indeed, after this matching method only one variable remains significantly different – Hispanic. Although it is statistically significant, the difference is small in magnitude with less than 6-thousandths of a difference (0.05446 versus 0.05963). Therefore, we also examine the Rubin's B and R for indications of balanced groups. After matching with replacement, the Rubin's B statistic is well below 30 at 6.1 and the Rubin's R statistics is well below 1.5 at 0.93. This shows that the supervised and unsupervised groups are well-balanced after using the matching with replacement technique and that it is appropriate to now calculate the treatment effects.

Step 3: Treatment Effects

The last step is to compute two types of treatment effects. First, the average treatment effect (ATE) is the "expected effect of treatment on a randomly selected person from the target population" (Apel and Sweeten 2010: 545). That is, across the target population of offenders, the ATE tells the anticipated effect of supervision. A second treatment effect is the Average Treatment Effect on the Treated (ATT) which is the expected effect of treatment among those individuals who are actually assigned to be in the treated group (Apel and Sweeten 2010). Essentially, the difference in the ATE and ATT involves the focus of the research question. In order to broadly examine the relationship between post-release supervision and recidivism, I report both the ATE and ATT in this paper and interpret them accordingly[6].

Gendered Differences Strategy

To examine differences by gender, I repeat the three step process outlined above on the subsample of males and females. First, I use individual logit models on each of the gender subsamples to predict each offender's

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[6] In order to account for the propensity scores being estimated and the use of nearest neighbor matching approach, I use Abadie-Imbens Robust Standard Errors. For a more technical and detailed discussion, see Abadie et al. 2004 and Abadie and Imbens 2006.

likelihood of being supervised after release. For males, the logit model is identical to that used for the overall sample except that it excludes the *female* variable and all interactions that involved the *female* variable because there are not any females in the model, yielding a subsample size of 128,178. The logit model for females, with a subsample size of 13,146, also excludes the *female* variable and *female* interactions. Additionally, it excludes the interaction between *time served* and *offense category*[7].

The results of the gender logit models can be found in Table 3 in Appendix D. After obtaining the propensity scores, I match supervised and unsupervised individuals within their gender, using the same nearest neighbor approach, both with and without replacement. I then examine the covariate balance across the groups, which can be found in Table 4 in Appendix E. Finally, I compute and interpret the treatment effects.

[7] This exclusion was necessary due to low cell numbers in the subcategories of the variables. Moreover, the results of the likelihood-ratio test were also nonsignificant indicating a preference for the more parsimonious model without the interaction

Chapter 4: Results

Overall Results

Figure 1 shows the average treatment effect (ATE) and the average treatment effect on the treated (ATT) for the overall sample. Recall that the average treatment effect is the expected effect of supervision for any individual offender. To calculate at the ATE, we look at the difference in rearrest and reconviction between those who are supervised and those who are unsupervised in the matched subsample. In contrast, the average treatment effect on the treated is the anticipated effect of supervision, among only those who are supervised (Guo and Fraser 2015). The first column in the figure is the differences for the unmatched sample indicated by UM. Using nearest neighbor matching with replacement, the second and third columns show the ATE and the ATT, respectively.

[Figure 1 about here]

Looking at rearrest, we can see that the difference between those who are supervised and those who are not supervised is -5.81%. This means, before matching supervision is associated with a 5.81% decrease in rearrest. This is in alignment with the expectations, not only of the criminal justice system, but of society overall. One of the main goals of parole is “helping an offender become a law abiding member of the community” as well as providing offenders with supervision and treatment in the community (Carlie 2002). A 5.81% decrease in rearrest in the unmatched sample shows that indeed, supervised offenders recidivate at lower levels than unsupervised offenders. However, before matching the supervised and unsupervised groups are very different on a number of characteristics. Therefore, it is impossible to determine if the difference in rearrest is due to being supervised after release or due to the unbalanced characteristics.

After achieving more comparable and balanced subsamples by PSM, this number is reduced. From the PSM models, supervision is associated with a statistically significant 4.07% decrease in rearrest. This is a 30% reduction in the estimated association from the unmatched analyses. This means that for any individual offender, we expect supervision to be associated with a 4.07% decreased chance of being rearrested. Among those who actually are supervised, the expected effect of supervision is a statistically significant 4.52% decrease in rearrest. Compared to the unmatched difference, this is a 22% reduction in the anticipated association, showing that the difference in the unmatched sample leads to overestimation of the anticipated effect of supervision.

This reduction between the unmatched and match subsample is expected since before matching, the groups are dissimilar suggesting there may be selection effects at work, sorting offenders into either the supervised or unsupervised groups. After matching and achieving more comparable groups, these selection effects are minimized allowing for the effects of post-release supervision to become more isolated. Therefore, the reduction between the matched and unmatched analysis is due to minimizing the selection effects and allowing the effects of post-release supervision remain.

These trends are echoed in the reconviction results. When looking at the unmatched sample, supervision is associated with a 5.55% decrease in reconviction. After matching, this anticipated effect is reduced by 27% to 4.05%. This means that after matching, supervision is anticipated to cause a 4.05% decrease in reconviction among any offender in the target population. Among those who are under supervision, we anticipate the effect of supervision to be a 4.50% decrease in reconviction. Similar to rearrest, the unmatched reduction overestimates the association between supervision and reconviction, and after matching the numbers are reduced. These anticipated effects, while small, are statistically different from zero. This indicates that supervision is associated with lower rearrest and reconviction and may even seem to cause this reduction.

Gendered Differences Results

Since past research shows gendered pathways into offending (Daly 1994; Sharp 2014) and reoffending (Salisbury and Van Voorhis 2009), it is necessary to examine any gendered effects for post-release supervision. Figures 2 and 3 show the treatment effects for each gender subsample. First, I examine the effects for males since these results closely resemble those of the overall sample and draw comparisons. Then, I examine the effects for females and contrast the numbers against those from the overall and male samples.

Figure 2 shows the ATE and ATT for both rearrest and reconviction for only the males in the sample. These results look similar to those of the overall model because the majority of individuals in the overall model are male. In the unmatched data, supervision is associated with a 6.38% decrease for males. However after matching, the anticipated treatment effect is a 4.11% decrease for any offender and a 4.26% decrease among those who are supervised after release. This translates to a 35% reduction in the estimate for the ATE and a 33% reduction for the ATT. Once again, without matching, the difference in the unmatched data overestimates the association between post-release supervision and rearrest. These trends are echoed in the reconviction results for males.

[Figure 2 about here]

The results for the female subsample are showcased in Figure 3. In the unmatched subsample of females, supervision is associated with a 5.15% decrease in rearrest. As expected, this is greatly reduced to a 3.48% decrease after matching, a 27% reduction between the unmatched and matched results. This means that after matching, supervision is associated with a 3.78% decrease in rearrest for any individual female offender in the target population. When looking at the ATT, we can see that among those who are supervised after release, the anticipated effect is only a 2.26% decrease, which is statistically indistinguishable from zero. This is a 56% reduction from the estimates gained from using the unmatched data.

For reconviction, these trends are echoed. The unmatched, data show a 3.79% decrease in reconviction for those who are supervised. However, after matching it is reduced to a 2.81% decrease for the ATE and a 3.18% decrease for the ATT. This shows that without matching, the data grossly overestimates the anticipated effect of supervision for women, especially when speculating about the effect among those who are supervised.

[Figure 3 about here]

The anticipated effects of supervision for women are almost half of what was found in the matched sample. For example, females have an anticipated reduction of 3.78% in rearrest for any individual offender, compared to 4.07% in the overall sample. Furthermore, among females who are supervised, the anticipated decrease is 2.26% compared to the overall supervised sample of 4.52%. This shows that the anticipated effect of supervision for women is quite weaker compared to the overall sample.

To examine any gendered differences, we compare the treatment effects for males and females. The anticipated effects of post-release supervision are greater for men. For any individual male, supervision is associated with a 4.11% decrease in rearrest but only a 3.78% decrease in rearrest for women. Among those who are supervised, the anticipated effect for men is a 4.26% reduction in rearrest while for women it is only a 2.26% decrease. Therefore, it seems there are gendered differences in post-release supervision between men and women.

Chapter 5: Discussion

Using propensity score matching to mimic randomization and get closer to causal statements, the analyses show that post-release supervision is associated with lower recidivism and may cause the decrease for both rearrest and reconviction. The influence of post-release supervision between supervised and unsupervised offenders is overestimated before matching. After matching and achieving equivalent groups, the anticipated reduction in recidivism is weaker, but still significant. This means that post-release supervision may play a role in causing a small but significant decrease in rearrest and reconviction for the overall sample.

The results for men and women echo the trends found in the overall data. After matching, the anticipated effects of post-release supervision on recidivism are less than before matching. This once again suggests that the differences between the supervised groups before matching overestimate the influence of post-release supervision on recidivism. For men, the magnitude of the difference after matching is similar to that of the overall data. This shows that for men, post-release supervision seems to help significantly reduce recidivism by a small amount.

For women, the treatment effects of supervision are smaller than those found in the overall or male data. Among females who are indeed supervised after release, the supervision does not significantly reduce rearrest. Put another way, among those who are actually receiving the supervision, there is no anticipated gain from being supervised. This finding, while shocking, is consistent with the much lower treatment effects found for all the female data and suggests that the implementation of post-release supervision may not be as successful for women as it is for men.

These findings coincide with the literature related to gendered pathways into crime. There are gendered differences in the entry into crime and reoffending and the challenges women face are often amplified from those of men (Chesney-Lind 1997; Daly 1992; 1994; Sharp 2014). The smaller treatment effects and nonsignificant finding for women suggests that the conditions of post-release supervision are not as successful in helping women address the issues they confront upon release and therefore escape the cycle of reentry. Supervision and programs rarely incorporate gender-differences in the reentry process (Bloom et al. 2002; Bloom and Covington 1998; Schram et al. 2006) and tailoring the conditions of supervision may increase the success of its influence on recidivism for women.

Furthermore, since many women offenders are mothers, responsibilities related to childcare and their dedication to rebuilding an identity as a good mother often act as protective factors against recidivism (Opsal 2011; Giordano et al. 2011; Kreager, Matsueda and Erosheva 2010; Sharp 2014). Therefore, it may be the case that supervision plays a less significant role for women because other factors, such as childcare responsibilities, already reduce their risk of reoffending. While the present data does not allow for this type of investigation, future research should gather information regarding childcare responsibilities in order to account for this possibility.

The findings not only reveal gender differences, but also that supervision is associated with only about a 4.5% reduction in recidivism. The cost for this supervision seems to be quite large. The 2016-17 Florida budget allows for about 9.8 million dollars to be used for post-release supervision services (Florida Policy Institute 2016), and nation-wide it is estimated to cost $2,750 per year for each parolee to be supervised (Petersilia 2011; Scott-Hayward 2009). Given that at the end of 2014, there were 856,900 offenders on parole (Kaeble, Maruschak, and Bonczar 2015), multiplying yields a figure of $2,356,475,000 spend on supervising parolees alone! This estimate does not even include the other types of post-release supervision such as conditional release, conditional medical release, control release, and addiction recovery supervision. Future research should conduct a cost-benefit analysis in order to investigate not only the return of lower recidivism rates when investing so much time, effort, and money, but also to examine if there are more effective ways to supervise offenders which would influence recidivism more.

While this paper offers insight into the relationship between post-release supervision and recidivism, there are some limitations. While the dataset allow for a varied set of demographic and crime-related variables as well as an ample follow-up period of 3 years, it does not include information during the supervision time-period, such as whether an offender was employed while being supervised. Future research should collect data during the supervision period in order to control for any differences among the offenders after release. Furthermore, there are often differences by location with policies sometimes changing from district to district. In order to account for this, future research should gather information regarding the district or county of the offender and control for these differences. Lastly, offenders may be reincarcerated due to technical violations of their supervision. While the present dataset does not allow for this measure of recidivism, future research should include this definition as well to investigate the overall effects of post-release supervision and any gendered differences.

Secondly, while having an encompassing definition of post-release supervision that includes a number of supervision types offers a broad examination of the relationship between supervision and recidivism, future research should examine this relationship on specific types of supervision in order to determine if some supervision types are more effective than others. Lastly, while propensity score matching does allow for more causal statements than other types of statistical methods, causality can never be fully reached with this type of data.

Conclusion

In conclusion, this analysis shows that offenders who are subject to post-release supervision tend to recidivate less and that the effect of the treatment manifests more strongly for male offenders than female offenders.

For any individual offender post-release supervision is expected to reduce recidivism by about 4%. Among those who are supervised, the anticipated gain is a 4.5% reduction in rearrest and reconviction. While men resemble the trends of the overall data, the numbers for women are much lower. Indeed, among supervised females, the data shows no significant reduction in rearrest. This suggests that the conditions of supervision may not be addressing the issues faced by women reentering society after incarceration. While many of these anticipated effects are significant, they are also small in magnitude, calling into question the utility of post-release supervision as it is now practiced. Future research should build upon these findings and examine the costs and benefits of post-release supervision while emphasizing the effective components.

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Appendix A: Descriptive Statistics

Table 1. Descriptive Statistics, by Gender as Means and Percentages

N	Overall 141,338	Males 128,183	Females 13,155	Male-Female Difference[1]
Female	9.3	-	-	
White	42.4	42.0	46.9	+
Hispanic	5.7	6.0	2.7	+
Offense Category				
Violent Crime	30.5	31.3	23.2	+
Property Crime	32.6	32.6	33.1	
Drug Crime	27.1	26.1	36.6	+
Other Crime	9.8	10.1	7.1	+
Employment Status				
Full-time Employed	54.5	57.2	28.4	+
Part-time Employed	8.7	8.8	6.9	+
Unemployed	30.4	27.4	59.7	+
Other Employed	6.9	6.5	5.0	+
High School (hs or more)	28.3	28.2	29.8	+
DNA Bank (yes)	47.7	49.5	30.5	+
Mean Year of Release	5.3	5.5	5.3	+
	(2.899)	*(2.889)*	*(2.981)*	
Mean Release Age	33.5 years	33.3 years	35.2 years	+
	(9.220)	*(9.319)*	*(8.006)*	
Mean Prior Arrests	5.6 arrests	5.7 arrests	5.1 arrests	+
	(3.696)	*(3.719)*	*(3.409)*	
Time Served				
0-0.99 years	31.3	29.9	44.7	+
1-1.99 years	27.9	27.7	29.7	+
2-4.99 years	27.9	28.7	20.7	+
5 or more years	12.9	13.8	4.9	+
Supervised (yes)	35.4	36.4	25.7	+
Rearrested (yes)	57.1	58.2	47.1	+
Reconviction (yes)	41.4	42.4	31.7	+

Note: Standard deviation reported in parenthesis.
[1]A two-sample *t*-test was preformed to determine significant mean differences between males and females. A plus sign indicates significant difference between males and females at $p < 0.001$ level.

Appendix B: Summary Statistics Balance

Table 2. Summary statistics balance before and after matching for overall sample

	Supervised	Unsupervised		
		Unmatched	Matched w/o Replacement	Matched w/ Replacement
N	50,074	91,259	50,074	29,795
Independent Variable				
Female	0.07	0.11*	0.08*	0.07
Control Variables				
White	0.44	0.42*	0.45*	0.44
Hispanic	0.05	0.06	0.06*	0.06*
Property Crime	0.30	0.34*	0.35*	0.31
Drug Crime	0.16	0.33*	0.17*	0.17
Other Crime	0.08	0.11*	0.09*	0.08
Part-time Employed	0.08	0.09*	0.08	0.08
Unemployed	0.28	0.32*	0.29	0.28
Other Employed	0.07	0.06*	0.07	0.07
Year of Release	5.22	5.32*	5.23	5.19
Release Age	34.28	33.08*	33.09*	34.18
High School	0.29	0.28	0.29	0.29
DNA Bank	0.56	0.43*	0.53*	0.55
Prior Arrests	5.86	5.49*	5.44*	5.83
Time Served				
1-1.99	0.24	0.30*	0.28*	0.23
2-4.99	0.34	0.25*	0.38*	0.34
5 or more	0.24	0.07*	0.13*	0.24
Interactions				
Female*Property Crime	0.02	0.04*	0.03*	0.02
Female*Drug Crime	0.02	0.04*	0.02	0.02
Female*Other Crime	0.00	0.01*	0.00	0.00
Female*High School	0.02	0.03*	0.03*	0.02
DNA Bank*Property Crime	0.16	0.15	0.19*	0.15
DNA Bank*Drug Crime	0.06	0.10*	0.06	0.06
DNA Bank*Other Crime	0.04	0.05*	0.04*	0.04
Prior Arrests*Property Crime	2.04	1.98	2.27*	2.06
Prior Arrests*Drug Crime	1.13	2.07*	1.18	1.11
Prior Arrests*Other Crime	0.47	0.62*	0.52*	0.47
Time Served*Release Age				
1-1.99	7.64	9.92*	8.83*	7.51
2-4.99	11.45	8.10*	12.62*	11.40
5 or more	8.90	2.52*	4.58*	9.05
Time Served*Property Crime				
1-1.99	0.08	0.10*	0.11*	0.07
2-4.99	0.10	0.09*	0.15*	0.10
5 or more	0.07	0.02*	0.04*	0.07

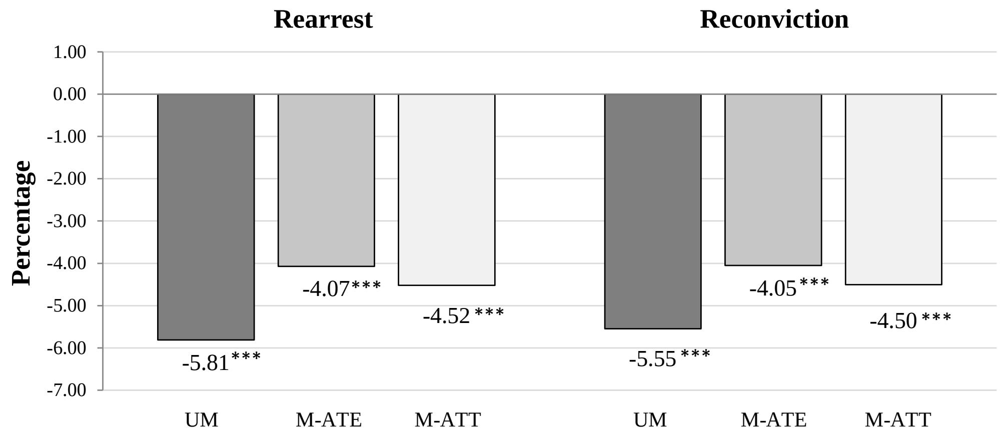
Table 2 continued. Summary statistics balance before and after matching for overall sample

	Supervised	Not Supervised		
		Unmatched	Matched w/o Replacement	Matched w/ Replacement
Time Served*Drug Crime				
1-1.99	0.04	0.11*	0.04	0.04
2-4.99	0.05	0.07*	0.06*	0.05
5 or more	0.04	0.01*	0.03*	0.03
Time Served*Other Crime				
1-1.99	0.02	0.03*	0.02	0.02
2-4.99	0.02	0.02	0.04*	0.02
5 or more	0.02	0.00*	0.01*	0.02
# of Significant Variables		34	28	1
Rubin's B		84.5	44.3	6.1
Rubin's R		1.35	1.58	0.93

Source: Criminal Recidivism in a Large Cohort of Offenders Released from Prison in Florida
Note: A two-sample *t*-test was preformed to determine significant differences between supervised and unsupervised groups. An asterisk (*) indicates significance at p<0.001level. If p-values <0.05 were included, the matched with replacement shows 6 significant differences with the supervised group. Due to lack of common support, 5 cases were excluded.

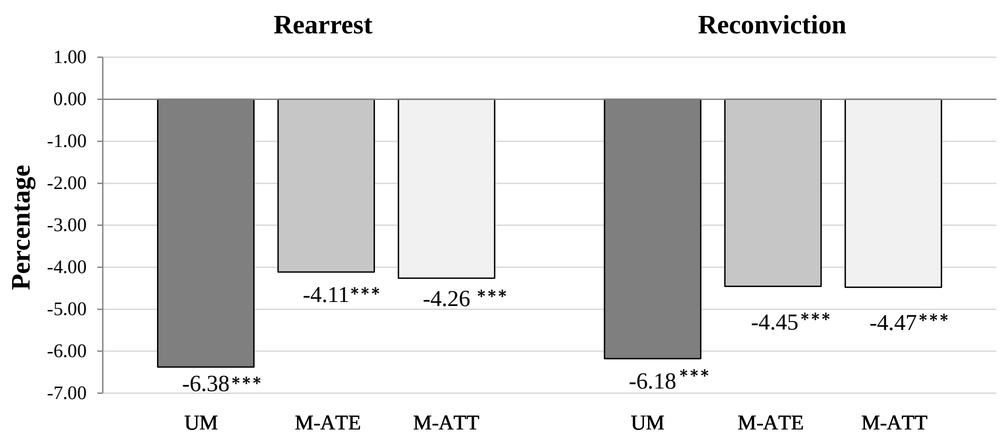
Appendix C: Percent Reduction between Groups

Figure 1. Percent Reduction Between Supervised and Unsupervised Groups, Overall Sample



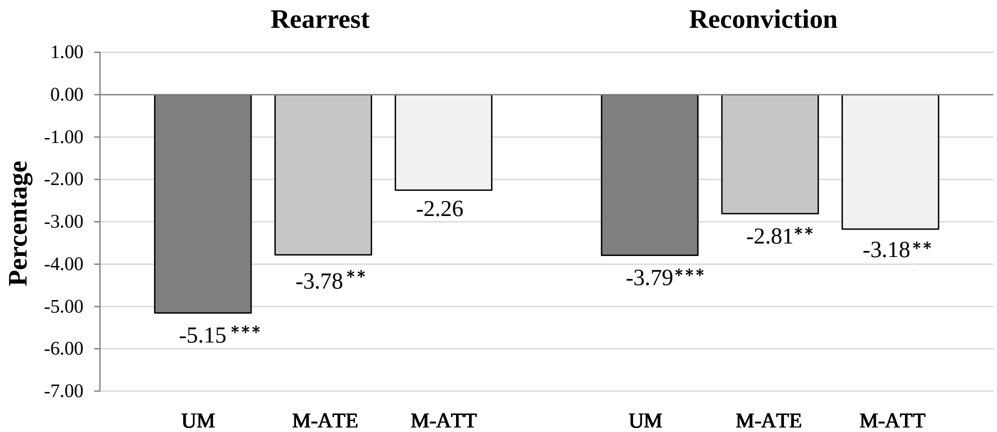
Note: UM indicates unmatched sample of 141,333, M-ATE indicates the average treatment effect for the matched sample of 79,848, and M-ATT indicates the average treatment effect on the treated for the matched sample of 79,848. ***p<.001 level.** p<0.01 *p<0.05 indicates significant difference from zero

Figure 2. Percent Reduction Between Supervised and Unsupervised Groups, Male Sample



Note: UM indicates unmatched sample of 128,178, M-ATE indicates the average treatment effect for the matched sample of 74,000, and M-ATT indicates the average treatment effect on the treated for the matched sample of 74,000. ***p<.001 level.** p<0.01 *p<0.05 indicates significant difference from zero.

Figure 3. Percent Reduction Between Supervised and Unsupervised Groups, Female Sample



Note: UM indicates unmatched sample of13,145, M-ATE indicates the average treatment effect for the matched sample of 5,773, and M-ATT indicates the average treatment effect on the treated for the matched sample of 5,773. ***p<.001 level.** p<0.01 *p<0.05 indicates significant difference from zero.

Appendix D: Logit Model for Propensity Scores

Table 3. Logit model predicting supervision for overall, male, and female samples, odds ratios

	Overall		Males		Females	
N	141,338		128,183		13,155	
Independent Variable						
Female (male)	0.69***	*0.029*	-	-	-	-
Control Variables						
White (non-White)	1.180 ***	*0.016*	1.17 ***	*0.016*	1.24 ***	*0.054*
Hispanic (non-Hispanic)	0.89 ***	*0.023*	0.88 ***	*0.024*	1.04	*0.136*
Property Crime (Violent)	0.55 ***	*0.022*	0.54 ***	*0.02*	0.83	*0.09*
Drug Crime	0.39 ***	*0.018*	0.38 ***	*0.02*	0.65 ***	*0.07*
Other Crime	0.70 ***	*0.039*	0.69 ***	*0.04*	0.79	*0.13*
Part-time Employed (Full-time)	0.93 ***	*0.021*	0.92 ***	*0.021*	1.01	*0.089*
Unemployed	0.94 ***	*0.013*	0.94 ***	*0.014*	0.95	*0.046*
Other Employed	1.02	*0.025*	1.02	*0.026*	1.05	*0.103*
Year of Release	0.99 ***	*0.002*	0.99 ***	*0.002*	1.01	*0.008*
Release Age	1.00 ***	*0.001*	1.00 **	*0.001*	1.00	*0.004*
High School (less than hs)	1.07 ***	*0.015*	1.07 ***	*0.015*	1.23 ***	*0.057*
DNA Bank (not in bank)	1.28 ***	*0.028*	1.30 ***	*0.030*	1.15	*0.092*
Prior Arrests	1.12 ***	*0.004*	1.12 ***	*0.004*	1.16 ***	*0.015*
Time Served (0-0.99 years)						
1-1.99 years	1.86 ***	*0.119*	1.89 ***	*0.126*	1.30	*0.296*
2-4.99 years	1.86 ***	*0.116*	1.83 ***	*0.118*	1.99 **	*0.483*
5 or more years	1.50 ***	*0.132*	1.44 ***	*0.131*	3.53 **	*1.621*
Model Intercept	0.29 ***	*0.015*	0.30 ***	*0.016*	0.19 ***	*0.033*
Interactions						
Female*Property Crime	1.23 ***	*0.068*	-	-	-	-
Female*Drug Crime	1.33 ***	*0.077*	-	-	-	-
Female*Other Crime	1.07	*0.101*	-	-	-	-
Female*High School	1.16 **	*0.055*	-	-	-	-
DNA Bank*Property Crime	1.00	*0.030*	1.01	*0.031*	0.90	*0.101*
DNA Bank*Drug Crime	0.91 **	*0.032*	0.91 *	*0.033*	0.89	*0.115*
DNA Bank*Other Crime	0.81 ***	*0.037*	0.82 ***	*0.039*	0.54 **	*0.117*
Prior Arrests*Property Crime	0.92 ***	*0.004*	0.92 ***	*0.004*	0.90 ***	*0.015*
Prior Arrests*Drug Crime	0.91 ***	*0.004*	0.91 ***	*0.005*	0.88 ***	*0.015*
Prior Arrests*Other Crime	0.89 ***	*0.006*	0.89 ***	*0.006*	0.89 ***	*0.024*
Time Served*Release Age						
1-1.99 years	0.99 ***	*0.002*	0.99 ***	*0.002*	1.00	*0.006*
2-4.99 years	1.00 *	*0.002*	1.00 *	*0.002*	1.00	*0.007*
5 or more years	1.02 ***	*0.002*	1.02 ***	*0.002*	1.01	*0.012*

Table 3 continued. Logit model predicting supervision for overall, male, and female samples, odds ratios

	Overall		Males		Females	
Time Served*Property Crime						
1-1.99 years	1.07	*0.044*	1.09 *	*0.047*	-	-
2-4.99 years	1.15 ***	*0.045*	1.18 ***	*0.049*	-	-
5 or more years	2.25 ***	*0.110*	2.33 ***	*0.117*	-	-
Time Served*Drug Crime						
1-1.99 years	1.00	*0.046*	1.03	*0.050*	-	-
2-4.99 years	1.18 ***	*0.052*	1.22 ***	*0.058*	-	-
5 or more years	2.82 ***	*0.156*	2.96 ***	*0.170*	-	-
Time Served*Other Crime						
1-1.99 years	0.93	*0.055*	0.95	*0.058*	-	-
2-4.99 years	1.04	*0.062*	1.06	*0.065*	-	-
5 or more years	2.54 ***	*0.196*	2.65 ***	*0.210*	-	-

Source: Criminal Recidivism in a Large Cohort of Offenders Released from Prison in Florida
Note: Reference categories reported in parenthesis next to variable. Standard errors reported in parenthesis and italicized next to odds ratios. Asterisks indicate significance: *** p<0.001 **p<0.01 *p<0.05

Table 3 shows the results for the logit model used to predict the propensity of supervision for each offender. The first column shows the results when generating propensity scores for the overall sample, while the second and third columns show the results for the gendered subsamples. In the overall model, many of the variables are significant in predicting supervision. Being female decreases the odds of being supervised after release while being white increases the odds of supervision compared to non-whites.

In the model for the male subsample, I exclude the *female* variable and its interactions since only men are included. These results echo the overall model with many of the variables remaining significant. Indeed, there is little difference in the magnitude of the effects between the overall and male models. In contrast, the female model looks very different. Many of the variables which are significant in the overall and male models are nonsignificant when predicting supervision for females. For example, being Hispanic significantly decreases the odds of supervision in the overall and male models but is nonsignificant in predicting supervision in the female model. The number of significant variables that are different between the male and female models supports the notion that these two groups are substantially different. This lends support for the idea of investigating the effects of post-release supervision separately for each group.

Appendix E: Summary Statistics Balance by Gender

Table 4. Summary Statistics balance across matched and unmatched sample for both males and females

	Males				Females			
	Supervised	Unsupervised			Supervised	Unsupervised		
		Unmatched	Matched w/o Replacement	Matched w/ Replacement		Unmatched	Matched w/o Replacement	Matched w/ Replacement
N	46,694	81,484	46,694	27,306	3,370	9,775	3,370	2,403
Control Variables								
White	0.43	0.41*	0.45*	0.44	0.47	0.47	0.49	0.49
Hispanic	0.06	0.06*	0.06*	0.06*	0.03	0.03	0.03	0.03
Property Crime	0.30	0.34*	0.36*	0.30	0.33	0.33	0.33	0.33
Drug Crime	0.16	0.32*	0.17*	0.16	0.25	0.41*	0.25	0.24
Other Crime	0.08	0.11*	0.09*	0.08	0.06	0.08*	0.06	0.07
Part-time Employed	0.08	0.09*	0.08	0.08	0.07	0.07	0.07	0.07
Unemployed	0.26	0.28*	0.26	0.26	0.58	0.60	0.58	0.58
Other Employed	0.07	0.06*	0.07	0.07	0.06	0.05	0.06	0.07
Year of Release	5.19	5.29*	5.21	5.19	5.53	5.55	5.55	5.60
Release Age	34.20	32.84*	32.91*	34.03	35.45	35.08	35.17	35.45
High School	0.29	0.28	0.28	0.29	0.32	0.29*	0.33	0.32
DNA Bank	0.58	0.45*	0.54*	0.57	0.38	0.28	0.36	0.37
Prior Arrests	5.90	5.56*	5.47*	5.82	5.35	4.96	5.17	5.35
Time Served								
1-1.99	0.23	0.30*	0.28*	0.23	0.29	0.30	0.30	0.29
2-4.99	0.34	0.25*	0.38*	0.34	0.28	0.18*	0.30	0.29
5 or more	0.25	0.08*	0.13*	0.25	0.10	0.03*	0.08	0.10
Interactions								
DNA Bank*Property	0.16	0.16	0.19*	0.16	0.10	0.09	0.10	0.10
DNA Bank*Drug	0.06	0.10*	0.07	0.06	0.05	0.07	0.04	0.04
DNA Bank*Other	0.04	0.05*	0.04	0.04	0.01	0.02	0.01	0.01

Table 4 continued. Summary Statistics balance across matched and unmatched sample for both males and females

	Males				Females			
	Supervised	Unsupervised			Supervised	Unsupervised		
		Unmatched	Matched w/o Replacement	Matched w/ Replacement		Unmatched	Matched w/o Replacement	Matched w/ Replacement
Prior Arrests*Property	2.05	2.01	2.30*	2.04	1.89	1.72	1.96	1.96
Prior Arrests*Drug	1.11	2.05*	1.17	1.07	1.42	2.20*	1.41	1.36
Prior Arrests*Other	0.48	0.65*	0.53*	0.48	0.32	0.39	0.35	0.37
Time Served*Release Age								
1-1.99	7.46	9.85*	8.78*	7.32	10.28	10.48	10.41	10.05
2-4.99	11.55	8.30*	12.70*	11.39	10.07	6.39*	10.44	10.10
5 or more	9.25	2.68*	4.68*	9.41	3.96	1.14*	3.17	4.00
Time Served*Property								
1-1.99	0.07	0.10*	0.11*	0.07	-	-	-	-
2-4.99	0.10	0.09*	0.15*	0.10	-	-	-	-
5 or more	0.07	0.02*	0.04*	0.07	-	-	-	-
Time Served*Drug								
1-1.99	0.04	0.10*	0.04	0.04	-	-	-	-
2-4.99	0.05	0.07*	0.07*	0.05	-	-	-	-
5 or more	0.04	0.01*	0.03*	0.04	-	-	-	-
Time Served*Other								
1-1.99	0.02	0.04*	0.02	0.02	-	-	-	-
2-4.99	0.02	0.02	0.04*	0.02	-	-	-	-
5 or more	0.02	0.01*	0.01*	0.02	-	-	-	-
# of Sign. Variables		30	24	1		8	0	0
Rubin's B		84.9	46.4	5.5		65.6	14.9	10.1
Rubin's R		1.29	1.55	0.94		1.77	1.46	1.01

Source: Criminal Recidivism in a Large Cohort of Offenders Released from Prison in Florida
Note: Reference categories reported in parenthesis. 5 males and 10 females excluded due to lack of common support. Asterisks indicate significance: * $p<0.001$. If included p-values <0.05, the matched with replacement males shows 5 significant differences and females show 1.

Table 4 shows the covariate balance as summary statistics for the male and female subsamples, before and after matching. For men, we can see that there are many differences between the supervised and unsupervised groups before matching. For example, 41% of those who are unsupervised in the unmatched sample are white but 43% of those who are supervised are white, a significant difference. Indeed, there are 30 significant differences across these two groups. After matching without replacement, the number of significant difference decreases slightly to 24. However, the Rubin's B and Rubin's R statistics continue to indicate poor balancing between the groups.

After matching with replacement, balanced is achieved. To be sure, in the matched, unsupervised sample, 44% are white which is not significantly different from the 43% in the supervised subsample. After matching with replacement, only one significant difference remains between the groups and the Rubin's B is reduced to 5.5 and the Rubin's R is reduced to 0.94, which both indicate well-balanced groups. This means that the matching with replacement model yields an unsupervised group which is balanced on the summary statistics with the supervised group, allowing for the treatment effects to be calculated.

For the females, the matched with replacement model is also the preferred model. Before matching there were 8 significant differences between the supervised and unsupervised groups. After matching without replacement, there are no significant differences. However, after matching with replacement, the Rubin’s B and Rubin’s R statistics are well within the preferred range indicating the groups are well-balanced on the summary statistics. Therefore, the matched with replacement model is the preferred matching strategy and the treatment effects can be calculated.